## **1** Appendix: Notational equivalence to the Yu and colleagues flanker model

Yu et al. use the following notation for their update:

$$P(s_2, M \mid X_t) = \frac{p(s_t \mid s_2, M)p(s_2, M \mid \mathbf{X}_{t-1})}{\sum_{s'_2, M} p(s'_t \mid s_2, M)p(s'_2, M \mid \mathbf{X}_{t-1})}$$
(1)

In their notation, the stimulus array is indexed such that  $s_2$  is the target and  $s_{1,3}$  are the flankers. Therefore, their  $s_2$  is simply our G. Their M is a trial compatibility or congruence variable, taking on the values of I(ncongruent) and C(ongruent). This gives a straightforward remapping from their joint probability space over target identity and congruence into our space of context and target:

Stimulus	С	$G == s_2$	М
SSS	S_S	S	Congruent
HHH	H_H	Н	Congruent
SHS	S_S	Н	Incongruent
HSH	H_H	S	Incongruent

Their prior  $P(s_2, M | \mathbf{X}_{t-1})$  is equivalent to our prior (it is simply the posterior from the previous timestep). Their input  $x_t$  is an input vector concatenating the input vectors from the target and two flankers,  $[x_1, x_2, x_3]$ , such that:

$$x_1(t) \sim (N)(\alpha_1 \mu_1 + \alpha_2 \mu_2, \sigma_1^2 + \sigma_2^2)$$
 (2)

$$x_2(t) \sim (N)(\alpha_1 \mu_2 + \alpha_2 \mu_1 + \alpha_2 \mu_3, \sigma_1^2 + 2\sigma_2^2)$$
(3)

$$x_3(t) \sim (N)(\alpha_1 \mu_3 + \alpha_2 \mu_2, \sigma_1^2 + \sigma_2^2) \tag{4}$$

Since the two flanker stimuli are always identical in this experiment, we can define  $\mu_c := \mu_1 = \mu_3$ and  $\mu_g := \mu_2$ . Next, we divide the means by  $\alpha_1$ , and map  $\frac{\alpha_2}{\alpha_1} := \alpha_m u$  to make  $x_2(t)$  equivalent to  $e^G$ . Since the three likelihoods are multiplied and the two flanker likelihoods are identical, updating jointly on  $[x_1, x_3]$  will be equivalent to updating twice on two draws of  $e^C$ .

Yu and colleagues also summarize their prior by defining  $\beta$  to be the prior probability of a congruent trial. We can define the priors in the following way to reflect this:

$$P_0(C = c_0, G = g_0) = \frac{\beta}{2}$$
(5)

$$P_0(C = c_0, G = g_1) = \frac{1 - \beta}{2}$$
(6)

$$P_0(C = c_1, G = g_0) = \frac{1 - \beta}{2} \tag{7}$$

$$P_0(C = c_1, G = g_1) = \frac{\beta}{2}$$
(8)

## 2 Full derivation of AX-CPT log likelihood expressions

In the internal context AX-CPT,  $t_{c^{on}} \neq t_{g^{on}}$ , so we index context samples using  $\ell$  and target samples using t. We therefore define  $l_t(t_x) = P(e_t^G \mid G = g_x)$  and  $l_\ell(c_x) = P(e_\ell^C \mid C = c_x)$  for the likelihoods, with  $x \in \{0, 1\}$  indexing stimuli. We can write the log likelihood for the two responses to the symmetric AX-CPT, divide numerator and denominator by the product of  $g_1$  and  $c_1$  likelihoods, and then rewrite the log likelihood ratios into the z term that evolve as biased Wiener processes in the continuum limit. Note that here the context and target walks start at different times.

$$\log Z = \log \frac{P_0(C = c_0, G = g_0) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_0) \prod_{t=t_g^{on}}^{\tau} l_t(g_0) + P_0(C = c_1, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_1) \prod_{t=t_g^{on}}^{\tau} l_t(g_1)}{P_0(C = c_0, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_0) \prod_{t=t_g^{on}}^{\tau} l_t(g_1) + P_0(C = c_1, G = g_0) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_1) \prod_{t=t_g^{on}}^{\tau} l_t(g_0)}}$$
(9)

$$= \log \frac{P_0(C = c_0, G = g_0) \prod_{\ell=t_c^{on}}^{\tau} \frac{l_\ell(c_0)}{l_\ell(c_1)} \prod_{t=t_g^{on}}^{\tau} \frac{l_t(g_0)}{l_t(g_1)} + P_0(C = c_1, G = g_1)}{P_0(C = c_0, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \prod_{t=t_g^{on}}^{\tau} \frac{l_t(g_0)}{l_\ell(g_1)}}{P_0(C = c_0, G = g_0) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} \sum_{t=t_g^{on}}^{\tau} \log \frac{l_t(g_0)}{l_t(g_1)} + P_0(C = c_1, G = g_1)}{P_0(C = c_0, G = g_1) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \sum_{t=t_g^{on}}^{\tau} \log \frac{l_t(g_0)}{l_t(g_1)}}}{(11)}$$

$$= \log \frac{P_0(C = c_0, G = g_0)e^{z_c^{\tau}}e^{z_g^{\tau}} + P_0(C = c_1, G = g_1)}{P_0(C = c_0, G = g_1)e^{z_c^{\tau}} + P_0(C = c_1, G = g_1)}$$

$$(12)$$

We can do the same for the asymmetric variant.

$$\log Z = \log \frac{P_0(C = c_0, G = g_0) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_0) \prod_{t=t_g^{on}}^{\tau} l_\ell(g_0)}{P_0(C = c_0, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_0) \prod_{t=t_g^{on}}^{\tau} l_t(g_1) + P_0(C = c_1, G = g_0) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_1) \prod_{t=t_g^{on}}^{\tau} l_t(g_1)}{P_0(C = c_1, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} l_\ell(c_1) \prod_{t=t_g^{on}}^{\tau} l_t(g_1)}{P_0(C = c_0, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \prod_{t=t_g^{on}}^{\tau} \frac{l_\ell(g_0)}{l_\ell(g_1)}}{P_0(C = c_0, G = g_1) \prod_{\ell=t_c^{on}}^{\tau} \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \prod_{t=t_g^{on}}^{\tau} \frac{l_\ell(g_0)}{l_\ell(g_1)} + P_0(C = c_1, G = g_1)}}$$

$$= \log \frac{P_0(C = c_0, G = g_0) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} \sum_{t=t_g^{on}}^{\tau} \log \frac{l_\ell(g_0)}{l_\ell(g_1)}}{P_0(C = c_0, G = g_1) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \sum_{t=t_g^{on}}^{\tau} \log \frac{l_\ell(g_0)}{l_\ell(g_1)}}}{P_0(C = c_0, G = g_1) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \sum_{t=t_g^{on}}^{\tau} \log \frac{l_\ell(g_0)}{l_\ell(g_1)}}}{P_0(C = c_0, G = g_1) \sum_{\ell=t_c^{on}}^{\tau} \log \frac{l_\ell(c_0)}{l_\ell(c_1)} + P_0(C = c_1, G = g_0) \sum_{t=t_g^{on}}^{\tau} \log \frac{l_\ell(g_0)}{l_\ell(g_1)}} + P_0(C = c_1, G = g_1)}}$$

$$= \log \frac{P_0(C = c_0, G = g_0)e^{z_c^{\tau}}e^{z_g^{\tau}}}}{P_0(C = c_0, G = g_0)e^{z_c^{\tau}}e^{z_g^{\tau}}}}$$
(16)